Reducing the Carbon Cost of Surgery: Examining RFID Localization and Tensor Decomposition for Surgical Tray Optimization

Lara Dincer, Duke University
Advised by Dr. Rory Turnbull, University of Leeds School of Mechanical Engineering

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How does healthcare contribute to Global Warming?

Healthcare systems account for 5% of global greenhouse gas emissions (Brunn et al., 2026). These figures range from 6-8% in Western countries, and are coupled with high resource consumption and overall large costs (Eussen et al., 2025). The three largest contributors to this carbon footprint are the operating room (OR), intensive care unit, and gastrointestinal endoscopy, with 20-30 % of hospital waste and 30-60 % of costs being associated with the OR (Eussen et al., 2025; Tee et al., 2024). Reusable surgical tools contribute considerably to this carbon footprint, primarily due to the sterilization process which accounts for 90% of their total impact (Tee et al., 2024). The amount of tools sterilized after a surgery depends solely on how many trays are opened during the process, with an estimated 78 - 87 % of instruments reported opened but unused, demonstrating a huge need for surgical tray rationalization (Hill et al., 2022).

How do we change this?

- Collect and analyze data on tool usage through Radio Frequency Identification Tags (RFID)
- Identify pertinent patterns in the data to create surgical tray configurations which prioritize increased efficiency and decreased waste

This study assembles a pipeline to be applied to data from simulation surgeries at SUSTAIN (Sustainability and Simulation Theatre for Academia and Industry) to accelerate the UK's National Health Services' Net Zero Carbon Emissions initiative.

Tool Localization with RFID

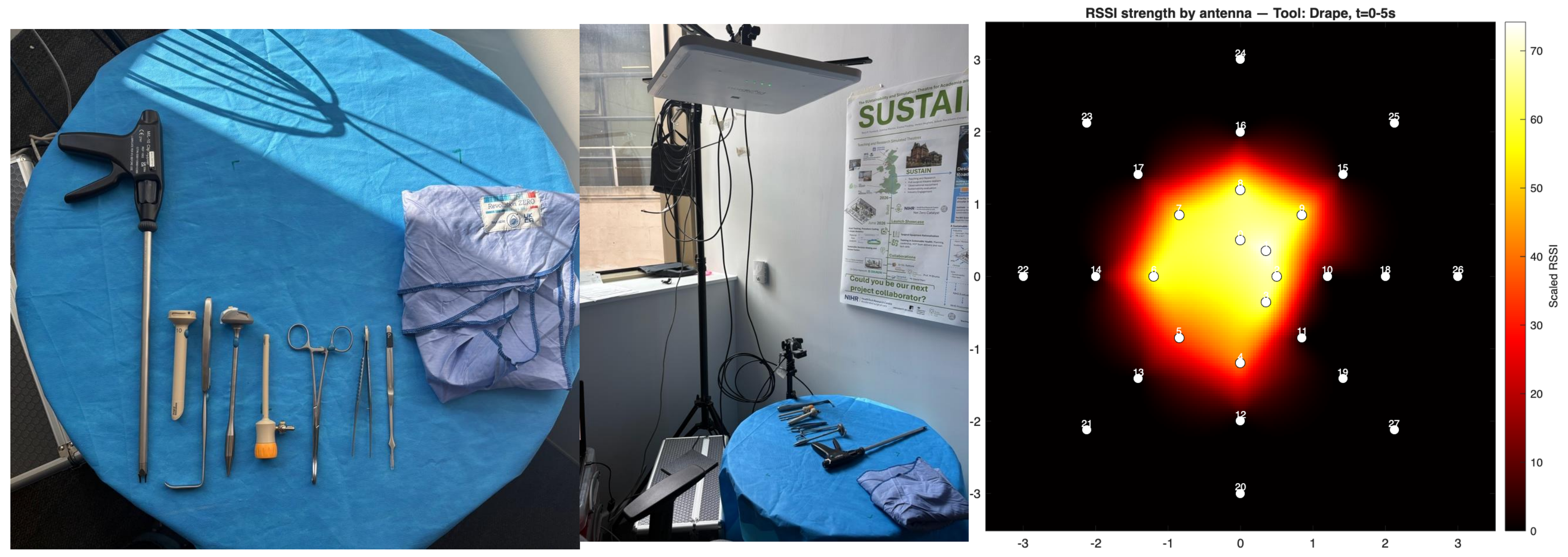

Figure 1. Antenna and Tray Set-up

Parameter	Description
editAccuracy	1 – (Levenshtein Distance*/ max(Predicted Sequence Length, True Sequence Length))
Precision	Longest Common Subsequence** Length / Number of Tools in Predicted Sequence
Recall	Longest Common Subsequence** Length / Number of Tools in True Sequence
F1	2((Precision)(Recall))/(Precisions + Recall)
Kappa (κ)	(Accuracy – Chance Agreement) / (1 – Chance Agreement)

Table 1. Metrics to evaluate localization algorithm (*minimum number of single-item changes to turn detected list into true order, **longest list of items that appear in both sequences in the same order)

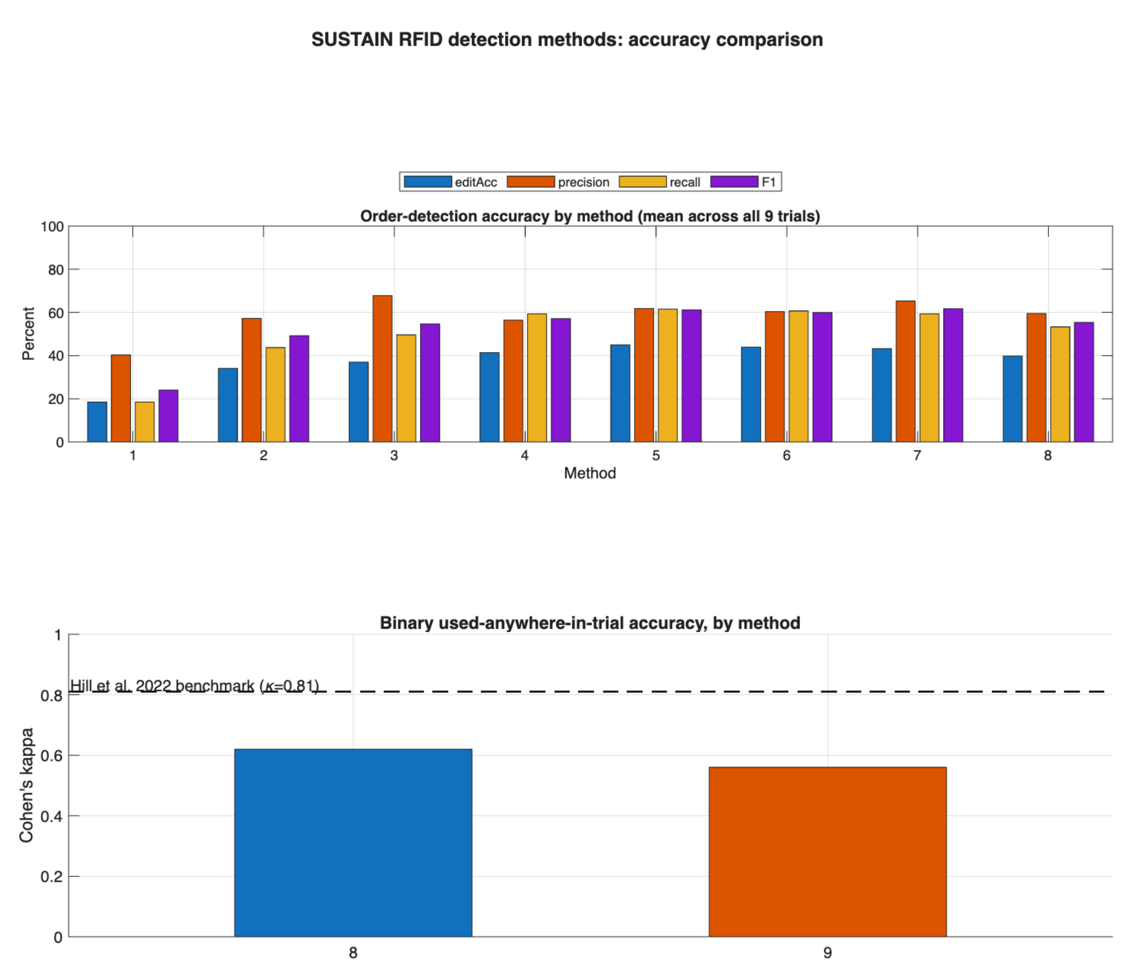

Figure 2. Accuracy Comparisons Across Methods of Detection. Method 1 predicted sequence by taking the highest signal at antenna 23 at any given point. Method 2 uses the reader's built in "tag left view" events. Method 3 uses busiest antenna per tool to identify exit events. Method 4 is Methods 2 & 3 combined. Method 5 defines an entrance zone with an RSSI signal threshold. Method 6L A logistic classifier trained to spot real pick ups. Method 7 pairs a fading signal near tray to an intensified signal near outer ring. Method 8 calculates a round trip between defined tray and surgical zones. Method 9 binarily use outer-ring antenna to identify pick ups.

Temporal Decomposition

Due to low accuracy of RSSI based sequence detection, accurately tracking sequence of tools is not a reliable tray rationalization method with the current set-up.

Temporal Decomposition can find temporal patterns without needing accurate localization, as it can identify similar signals across tools.

Pipeline to Analyze a Folder of Different Surgeries

Format raw RSSI signal into 3D matrix, made up of a dimension for surgery number, time, and RSSI signal

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Use CP/PARAFAC decomposition to identify Principal Components (PCs) elucidating trends in the data. Note the loading score of each tool, to identify which tools are most associated with a PC, and the temporal trajectory of each PC dictating its importance throughout time.

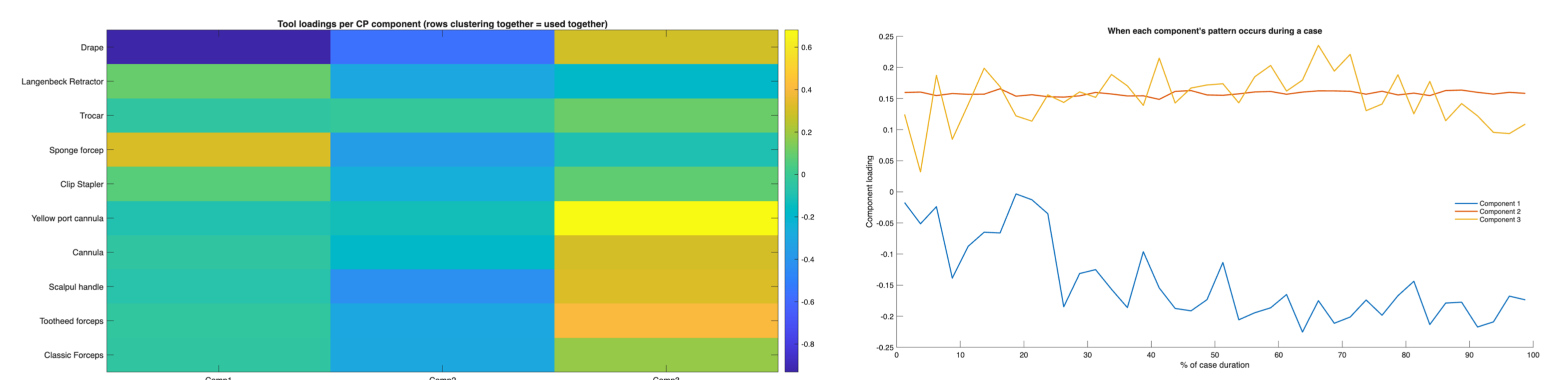

Figure 3. Tensor Decomposition Output, tool loadings graphed (above) and temporal strength of the pattern throughout the experiment (below)

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Graph each individual surgeries' Principal Component Score to see if there is a statistically significant association between the PC and feature (e.g. carbon count, surgery efficiency)

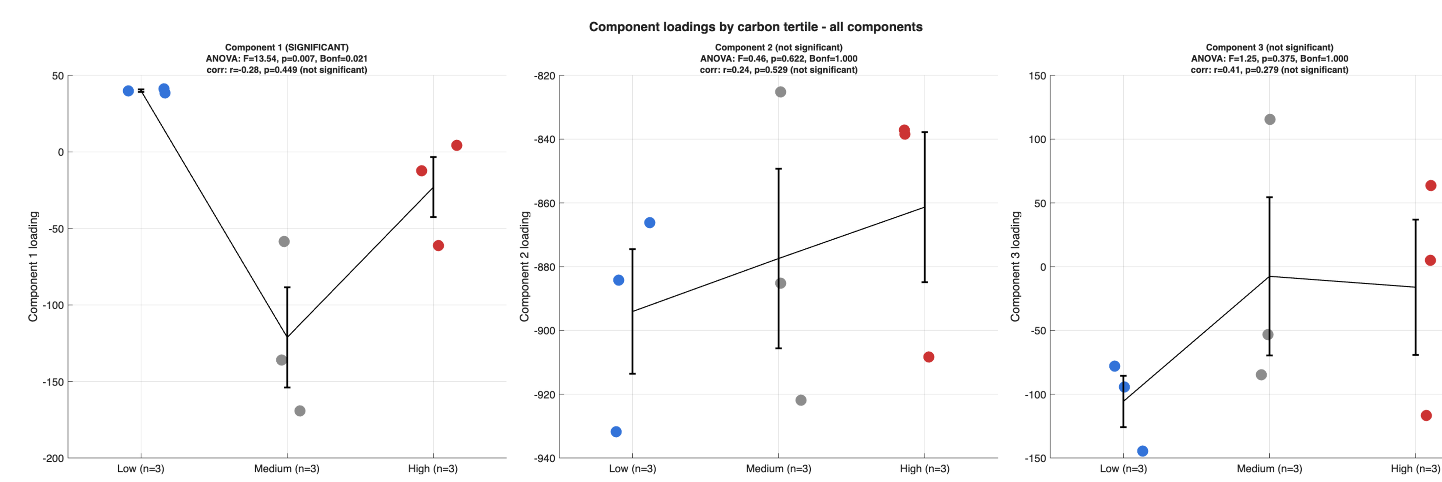

Figure 4. Association of each component with high/low/medium carbon cost surgeries based on preliminary data

References

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